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Demand, utilization, and supply of community smart senior care services for older people in China

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Abstract

Objective: Although smart senior care services offer numerous benefits, they have not yet gained widespread acceptance among the general populace, particularly seniors. Numerous related issues have surfaced, with the structural imbalance between supply and demand being most prominent. Currently, there is a lack of research distinguishing between the various categories of demand for smart ageing services and the associated behaviors of older individuals. In this study, we aimed to identify the types of demand and utilization of smart senior care services among Chinese older adults to understand their diverse characteristics and the factors that facilitate certain behaviors. We also analyzed the imbalance between supply and demand for smart senior care services and explored the factors influencing it, thereby providing a reference for optimizing smart senior services.

Methods: We conducted a cross-sectional study from January to March 2023 and analyzed 1037 valid questionnaires. Three types of smart senior care services were investigated: intelligent information, intelligent consultation, and intelligent monitoring. We identified the demand, utilization, and supply of these services among older individuals. Latent class analysis (LCA) was used to differentiate the heterogeneity of older adults in terms of service demand and utilization. Factors influencing service preferences were analyzed using binary logistic regression based on Andersen's behavioral model.

Results: Based on the LCA findings, service demand, and utilization were divided into two categories: positive demand (desire to use the services) or negative demand, and taking action or negative action to use the services. The persons with high demand but low utilization comprised the largest number of older people in this study (69.35%). The results indicated that the number of children (odds ratio (OR) = 1.491), community-provided smart devices (OR = 1.700), number of chronic diseases (OR = 1.218), and self-care capacity (OR = 0.214) are associated with positive demand. Meanwhile, pre-retirement employment, income sources, community device provided, community promotion, region, and self-care ability were significant predictors ($p < 0.05$) of taking action to use the services. In terms of community supply outcome, income situation had a significant effect on intelligent information services. Income sources were associated with intelligent information and intelligent monitoring services. Pre-retirement employment and housing type variables showed effect on IC services. Community promotion and self-care ability were associated with all three types of service supply ($p < 0.05$).

Conclusion: Older adults expressed a strong demand for smart ageing services; however, difficulties using smart technology remain a serious problem. Further investigation of how family support contributes to the perception and use of care services for older people is needed. Specific policies, such as financial assistance, should be established to support service use. Communities should expand their support and promotion of smart ageing services, focusing on enhancing digital health literacy among seniors to facilitate product utilization. Furthermore, personalized recommendations and applications tailored to the physical conditions of older adults are essential.

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Introduction

According to the National Bureau of Statistics of China's 2023 report, the population aged 65 years and above comprised 14.9% of the total population, with an old-age dependency ratio of 21.8%.[1] By 2035, the population aged 60 years and above in China is expected to exceed 400 million, accounting for over 30% of the total population, indicating a profound ageing phase.[2] The rising proportion of older adults, coupled with diminishing family sizes and the proliferation of empty-nest families, poses serious challenges in meeting the demand for aged-care services and alleviating the societal burden of senior care.[3,4] However, the burgeoning growth of the Internet has provided a robust technological foundation for senior care, allowing for innovative approaches to supplying smart senior care services.[5]

Smart senior care services represent the integration of cutting-edge technologies such as the Internet of Things, information technology, big data, and cloud computing in the domain of geriatric care. These services aim to deliver advanced care solutions[6] and encompass three main categories: (1) intelligent information (II), including access to medical information, knowledge and education, and online communication; (2) intelligent consultation (IC), such as telemedicine and consultation services; and (3) intelligent monitoring (IM), which involves the recognition of real-time activity, localization, and remote monitoring.[7,8] The objective of these services is to provide detection, monitoring, socialization, and other functions through smart devices by accessing medical information and medical data.[9] For example, telemedicine, online health counseling, and smart living aids can improve the quality of life of older people and offer novel approaches to disease prevention, health management, and senior care services.[10,11] At the individual level, these models prioritize personalized senior care demands, thereby improving service quality and satisfaction.[12] At the societal level, smart senior care services promote innovation in senior care models and enhance the overall efficiency of senior care services by integrating resources and optimizing management.[13]

The practical implementation of intelligent senior care has commenced in many countries. Research indicates that China's smart ageing services have progressed through four stages of development: the seed stage, startup stage, development stage, and popularization stage.[6] Despite the numerous benefits of smart ageing services, they have yet to gain widespread adoption among the general public or seniors.[14] Numerous issues have surfaced, with the gap between supply and demand being most prominent.[4,15] On the one hand, there is a shortage of smart senior care products and an insufficient supply of community-based smart senior care services. For example, studies have pointed out the high demand for medical and emergency services among older persons, but the availability of services is inadequate[16] On the other hand, older adults have limited knowledge about smart senior care, leading to low demand for these services.[4] This gap between these two aspects has led to practical difficulties, such as the inability of smart senior care service products to meet the actual needs of older people and a low degree of market adoption.[5,15] Therefore, it is crucial to consider the development of smart senior care services from the perspectives of both supply and demand.

From the perspective of older adults, existing research has conducted more studies on older people's awareness, willingness, and adoption of smart senior care. Adoption behavior has been studied using the UTAUT and TAM models, highlighting the two key variables of perceived usefulness and trust.[14,17–19] It has also been identified that the experiences of older people are key to influencing long-term adoption behavior.[20] Based on the acceptance and adoption of the services, researchers continue to measure actual demand and utilization. A study in Macao found that older adults' use and need for smart senior care were generally low, and that they were more concerned about spiritual needs, while the caregivers were more concerned about the health and safety of older adults.[7] The survey in the Lanzhou region of China found that 33.75% of participants expressed the need for intelligent services.[21] It has also been suggested that emotional attachment, need compatibility, cues to use, proficiency to use, input of resources, and support are factors that influence the long-term use of technology by older people.[22] In terms of research on facilitators, existing studies generally recognize that factors such as gender, age, number of children, living arrangements, affordability, healthcare security, health status, chronic conditions all influence older people's behavior toward smart senior services.[18,21,23–26] In terms of service supply, Zhang et al.[6] presented an overview of the current situation and development of smart homes for Chinese older adults, identifying four stages of development: seed, startup, development, and popularization. Some scholars have also used quantitative methods to measure the quality of smart senior care service platforms and the coupling coordination development indicators.[12,15] Overall, it is evident that the research on older people's demand for and use of smart ageing services is diverse and fragmented. Current research has several limitations. Specifically, most studies have examined only one aspect of the elderly's demand, utilization, and community supply. Combined studies that comprehensively analyze the supply–demand and demand-utilization gaps are lacking. Second, few previous studies have examined whether there are different demand or utilization subgroups in smart senior care services for the elderly. Finally, the lack of an integrated framework for analyzing influencing factors results in fragmented policy relevance.

For the above reasons, a comprehensive and in-depth analysis of both service supply, demand and utilization is essential to ensure the better supply of community-based smart senior services. Previous studies have identified a range of sociodemographic factors that affect older people's behavior, suggesting the possible existence of subgroups among elderly population. The characterization of the latent heterogeneity of older people will help to inform the development and customization of more targeted improvements.[27] Latent class analysis (LCA) is a form of person-centered mixture modeling that identifies latent subpopulations (classes) based on the pattern of their responses to observed categorical variables.[28] The aim of this study was to identify the types of demand and utilization of smart senior care services among Chinese older adults using LCA. These findings helped us understand the heterogeneous characteristics of different types of older people and explore the factors that influence it. At the same time, the Andersen's behavioral model, an internationally recognized framework for health service research, posits that the utilization of health services is influenced by predisposing, enabling, and need factors.[29] This model has garnered widespread application in community-based service delivery and care services utilization,[30–32] and also in studies for mobile phone applications.[33] Effective recommendations were provided to inform policy makers on how to optimize services and reform the health system. Therefore, this study adopted the Andersen's behavioral model as the analysis framework to explore the facilitators of behavior in older adults. Overall, in this study we seek to answer the following questions: (1) What is the proportion of the elderly population who demand, have used and provided smart senior care services in China? (2) What is the pattern of demand and utilization of elderly population responses to smart senior care services using latent class analysis? (3) What are the factors that contribute to the demand, utilization, and supply of community-based smart senior care services? The findings offer theoretical and practical insights for advancing the smart senior care model in China.

Methods

Data sources and study design

We conducted a cross-sectional questionnaire survey between January and March 2023. Due to the difficulties of sampling during the period of the epidemic, the purposive and convenience sampling method was adopted. Given the close association between the development of smart senior care services and local economic levels, this study preferred to investigate first- and second-tier cities, as well as developed third-tier cities in China. Firstly, a pilot presurvey was implemented prior to the formal study, whereby 80 older adults from the community who met the study criteria were screened for face-to-face questionnaires, and questionnaires were checked for completion and collected on-site. Eighty questionnaires were successfully distributed and 49 were validly collected. The content and language presentation of the questionnaire was slightly adjusted to take into account the problems that existed during the pilot test. Secondly, we distributed the questionnaire nationwide through wenjuan.com. Population that met the study criteria were included to complete the questionnaire. At the onset of the online questionnaire, participants were informed of the study objectives and were assured that they could withdraw from the study at any time for any reason. All participants confirmed their informed consent prior to completing the questionnaire.

The eligibility criteria for participation were as follows: (1) age 60 years or older, (2) residency in the district for at least 6 months, (3) ability to understand the questions and answer truthfully, and (4) capacity to provide informed consent and participate voluntarily. The exclusion criteria comprised the following: (1) questionnaires completed in less than 60 seconds, (2) participants aged less than 60 years, and (3) individuals who failed to meet the aforementioned participation conditions. A total of 1100 questionnaires were distributed, and following the exclusion of unqualified and invalid responses, 1037 valid questionnaires were included in the analysis, representing a valid response rate of 94.27%.

Measurements

Based on the existing literature, a questionnaire on community-based smart senior care services was developed through group discussions. The questionnaire contains two main sections. The first section focused on the demographic characteristics of the respondents based on the Andersen's behavioral model.[18,21,23–26,32,34] The second section assessed the demand, utilization, and community supply of community-based smart senior care among older adults.[7,34]

Outcome variables

This study examines three types of community-based smart senior care services: II, IC, and IM. The questionnaire assessed service demand, community supply, and utilization among older adults. Participants were asked three questions: (1) Do you need this type of service? (2) Does the community provide this type of service? (3) Have you used this type of service?

For the first question regarding needs, the option "I don't need this type of service" was classified as "no potential need" (assigned a value of 0). The options "may need," "I need this type of service," and "It fits my actual needs very well" were grouped under "has a potential need" (assigned a value of 1). For the service supply question, the option "Community does not provide" was defined as "no supply" (assigned a value of 0) while "Community provides" was categorized as "supplied" (assigned a value of 1). Regarding service utilization, the options "Not available in the community and cannot be used," "I have not used it," and "I want to use it and am ready to do so" were classified as "no action" (assigned a value of 0). The options "Already use it but with some difficulty" and "It is very convenient and I will use it often" were grouped under "Actual use" (assigned a value of 1). This supply–demand imbalance can manifest in two ways: unmet demand (existing need with no available service) and unutilized supply (available service with no corresponding need). The Cronbach's alpha and Kaiser–Meyer–Olkin values were used to determine the reliability and validity of the questionnaire. The results showed that the Cronbach's alpha was 0.782, while the Kaiser–Meyer–Olkin value was 0.761 ($\chi^2 = 1751.809$, $p < 0.001$), which may indicate that the questionnaire has an acceptable structural validity (Table 1 for detail).

Independent variables

An analytical framework was constructed based on the Andersen behavioral model to explore the demand, utilization, and supply of community-based smart ageing services among older adults. The predisposing factors encompass demographic characteristics such as sex, age, marital status, and number of children, reflecting the individual attributes of older persons. The enabling factors include the appropriate community, individual, and familial resources available for accessing smart senior services. Given the characteristics of the senior care model in China, where the family plays a pivotal role, the enabling resources in this study were expanded to include not only individual and familial resources but also societal resources. Need factors relate to the individual's perceived health and functional status or how others describe their health,[35] including self-assessed ability and the presence of chronic diseases. The variable assignments are detailed in Table 2.

Data analysis

The data were collated in an Excel sheet, and descriptive statistics were performed using IBM SPSS 22.0. Categorical variables are presented as n (%) and continuous variables as mean ± standard deviation (SD).

To discern the heterogeneity among older individuals in terms of their potential demand and actual use, the LCA was employed. The key indicators for evaluating model fit included log likelihood, Akaike's information criterion (AIC), the Bayesian information criterion (BIC), the adjusted BIC (aBIC), the Lo–Mendell–Rubin likelihood ratio test, and the bootstrap likelihood ratio test (BLRT). Generally, lower values of AIC, BIC, and aBIC suggest a better model fit. Entropy served as a measure of classification accuracy, with higher values indicating superior classification quality. The single-category model served as the baseline, and the number of categories was increased

Table 1. Variable assignment of smart senior care services, n (%).

Type	Categories	Intelligent information	Intelligence consultation	Intelligent monitoring
Services demand	No potential demand	176 (19.1)	170 (19.2)	156 (17.8)
	Have a potential demand	745 (80.9)	714 (80.8)	721 (82.2)
Services utilization	No action	838 (91.0)	757 (85.6)	775 (88.4)
	Actual used	83 (9.0)	127 (14.4)	102 (11.6)
Services supply	No supply	488 (53.0)	509 (57.6)	521 (59.4)
	Supplied	433 (47.0)	375 (42.4)	356 (40.6)
Supply–demand imbalance	Unmet demand	391 (42.5%)	388 (43.9%)	418 (47.7%)
	Unutilized supply	79 (8.6%)	49 (5.5%)	53 (6%)

Table 2. Definition and assignment of independent variables.

Category	Variable	Assignment
Predisposing factors	Sex	Woman = 0, man = 1
	Age	80 and above = 0, 70–79 = 1, 60–69 = 2
	Marriage	Other = 0, married = 1
	Child number	Number
Enabling factors	Education	Primary school and below = 0, junior high school = 1, high school/vocational secondary school = 2, college/junior college and above = 3
	Pre-retirement employment	No job = 0, agriculture related = 1, individually owned business = 2, private enterprise = 3, public institutions = 4
	Income situation	3000 and below = 0, 3001–5000 = 1, 5001–8000 = 2, 8001–12,000 = 3, over 12,000 = 4
	Income sources	Retirement pension = 0, child support = 1, savings, financial investments, etc = 2, government grants and subsidies = 3, labor work = 4
	Household registration	Rural = 0, urban = 1
	Housing type	Self-purchased commercial housing = 0, child purchased commercial house = 1, self-built house/rural owned house = 2, demolition and resettlement house/unit welfare house = 3, rental housing/senior apartment/other = 4
	Medical insurance	Self-funded = 0, New Agricultural Cooperative Medical Insurance (NACMI) = 1, Urban and Rural Residents Basic Medical Insurance(URRBMI) = 2, Urban Employees Basic Medical Insurance(UEBMI) = 3, free medical care = 4
	Community smart device provided (community device)	No = 0, yes = 1
	Community promotional activities conducted (community promotion)	No = 0, yes = 1
	Region	Western region = 0, central region = 1, eastern region = 2
Need factor	Chronic number	Number
	Self-care ability	Completely unable = 0, partially self-care = 1, basically = 2, completely = 3

gradually. The fitting indices of each model were compared, and the optimal model was determined based on the actual clinical context.[30,36,37] The LCA analysis was conducted using Mplus 8.

Additionally, binary logistic regression analysis was conducted to examine the influencing factors, incorporating Andersen's behavioral model, across four domains: the distribution of latent categories in potential demand, the distribution of latent categories in actual use, older people's needs, and service supply. Categorical variables were analyzed using the chi-square test, and continuous variables underwent one-way analysis of variance. The statistical significance threshold was set at $p < 0.05$.

Ethical statement

This study was approved by the Ethics Commit of Nanjing Medical University (Number (2022)960) accordance with the Declaration of Helsinki. All participants have signed informed consent forms prior to the study.

Results

Participant characteristics

Table 3 presents the detailed sociodemographic characteristics of the 1037 survey respondents, including predisposing factors such as sex (60%, male), age (68.6% aged 60–70 years), marital status (90.7% married), and average number of children (1.67). With regard to enabling factors, 37.4% had a high school education level, 83.1% had urban household registration, 80.9% derived their income from a retirement pension, and 57.0% owned self-purchased commercial housing. Meanwhile the survey respondents were predominantly from the eastern China, with 824 people (79.5%). In terms of community action, 77.2% of communities provided smart devices, and 82.9% conducted promotional activities. Regarding needs, the mean number of chronic diseases was 1.396, and 73.3% of participants had complete self-care ability.

Latent categories of smart senior care services

As presented in Table 4, the results for both potential demand and actual utilization of services indicated that a two-class model was optimal. This decrease in AIC, BIC, and aBIC values, along with the increase in entropy and statistically significant LMRT and BLRT values, indicated a better two-class model. However, when the number of categories was further increased to three, the AIC, BIC, and aBIC values increased, and the entropy value decreased. Notably, the LMRT and BLRT values were not statistically significant in this case. Based on a comprehensive analysis of these statistical indicators, both the demand for and utilization of smart senior care services were ultimately categorized into two distinct groups.

Regarding service demand, the first latent class, termed "positive demand" type, comprised 774 participants (79.88%), exhibiting a probability of demand for all three services exceeding 0.9. Conversely, the second latent class, the "negative demand" type, encompassed 195 participants (20.12%), with probabilities for the three services ranging from 0.10 to 0.26. In terms of service utilization, the first latent class, defined as "taking action" type, consisted of 102 individuals (10.53%), demonstrating the highest probability for all three intelligent care services, ranging between 0.64 and 0.95. The remaining class, comprising 867 individuals (89.47%), was labeled "negative action" type, exhibiting the lowest probability for all three services, falling below 0.1. Detailed information on the model is presented in Table 5 and Figure 1. The intersection of the categories of potential need and actual utilization reveals four distinct types. Firstly, the "positive demand–taking action" type (102 persons, 10.53%), which refers to persons with high demand and high utilization. Secondly, the "positive demand–negative action" type (672 persons, 69.35%), which refers to persons with high demand but low utilization. Then, the "negative demand–negative action" type (195 persons, 20.12%), representing those with low demand and low utilization. Finally, the type of "negative demand–taking action" (0 persons), meaning those who have low demand but high utilization.

Analysis of factors influencing latent category

Using LCA, the factors that facilitate both the "positive demand" type and "taking action" type were investigated (Table 6). Binary logistic regression analyses were conducted, using the Andersen's behavioral model as the analytical framework. When considering positive demand type as the dependent variable, the number of children emerged as a significant influencing factor (odds ratio (OR) = 1.491, $p < 0.05$). Older individuals who were previously employed in private enterprise (OR = 2.086, $p < 0.05$) were more likely to exhibit a positive demand compared to those without job. Furthermore, older people residing in self-built or rural-owned houses were less likely compared to those with self-purchased commercial housing (OR = 0.431). Additionally, having smart services provided in the community increased the likelihood of belonging to the positive demand type (OR = 1.700). In terms of needs factors, a higher number of chronic diseases and lower self-care capacity were associated with a greater likelihood of belonging to the positive demand category.

In the logistic analysis of the "taking action" type model, pre-retirement employment, income sources, community device provided, community promotion, region and self-care ability emerged as significant predictors. Specifically, employment in agriculture-related fields (OR = 4.469), income from child support (OR = 4.159), savings (OR = 4.354), and labor work (OR = 3.932) were predictive factors of taking action. Furthermore, residing in a community that provides smart devices (OR = 3.307) and conducts promotional activities (OR = 3.108) was associated with increased action. Higher self-care ability (OR = 0.438) was inversely related to taking action, indicating that those with lower self-care ability were more likely to demonstrate active utilization of smart senior care services.

Analysis of factors influencing the supply and demand for services

The results of logistic analysis presented in Table 7 revealed several significant predictors of demand for senior care services. Specifically, the number of children, pre-retirement employment status were influential factors for IC and IM services. The income situation and income sources were factors for II services. The housing type, medical insurance, and region as significant predictors for IC services. The community device provided was for IM services and self-

Table 3. Characteristics of the sample (n = 1037).

Variables	Categories	n/Mean	%/SE
Sex	Woman	415	40.0
	Man	622	60.0
Age	80 and above	62	6.0
	70–79	264	25.5
	60–69	711	68.6
Marriage	Other	96	9.3
	Married	941	90.7
Child number		1.677	0.946
Education	Primary school and below	156	15.0
	Junior high school	241	23.2
	High school/vocational secondary school	388	37.4
	College/junior college and above	252	24.3
Pre-retirement employment	No job	137	13.2
	Agriculture related	122	11.8
	Individually owned business	192	18.5
	Private enterprise	332	32.0
	Public institutions	254	24.5
Income situation	3000 and below	185	17.8
	3001–5000	238	23.0
	5001–8000	274	26.4
	8001–12,000	229	22.1
	Over 12,000	111	10.7
Income sources	Retirement pension	839	80.9
	Child support	61	5.9
	Savings, financial investments, etc	63	6.1
	Government grants and subsidies	17	1.6

(continued)

Table 3. Continued.

Variables	Categories	n/Mean	%/SE
	Labor work	57	5.5
Household registration	Rural	175	16.9
	Urban	862	83.1
Housing type	Self-purchased commercial housing	591	57.0
	Child purchased commercial house	109	10.5
	Self-built house/rural owned house	141	13.6
	Demolition and resettlement house/unit welfare house	164	15.8
	Rental housing/senior apartment/other	32	3.1
Medical insurance	Self-funded	5	0.5
	NACMI	158	15.2
	URRBMI	343	33.1
	UEBMI	426	41.1
	Free medical care	105	10.1
Community smart device provided	No	236	22.8
	Yes	801	77.2
Community promotional activities conducted	No	177	17.1
	Yes	860	82.9
Region	Western region	106	10.2
	Central region	107	10.3
	Eastern region	824	79.5
Chronic diseases number		1.396	1.221
Self-care ability	Completely unable	6	0.6
	Partially able	39	3.8
	Basically able	232	22.4
	Completely able	760	73.3

Table 4. Fitting information for potential categories.

Model	AIC	BIC	aBIC	entropy	LMR	BLRT	Class probability
Services demand							
1	2591.229	2605.858	2596.330	–	–	–	1
2	2045.560	2079.694	2057.462	0.868	$p < 0.001$	$p < 0.001$	0.789/0.211
3	2053.560	2107.199	2072.263	0.660	0.500	1.000	0.144/0.677/0.178
Services utilization							
1	1921.985	1936.614	1927.086	–	–	–	1
2	1417.721	1451.855	1429.623	0.930	$p < 0.001$	$p < 0.001$	0.883/0.117
3	1425.721	1479.360	1444.424	0.844	0.488	1.000	0.081/0.844/0.074

aBIC: the adjusted the Bayesian information criterion; AIC: Akaike's information criterion; BLRT: bootstrap likelihood ratio test.

Table 5. Latent class probabilities and conditional probabilities.

Variables	Services demand		Services utilization	
	Positive demand type	Negative demand type	Taking action type	Negative action type
Intelligent information	0.952	0.242	0.641	0.015
Intelligence consultation	0.977	0.109	0.948	0.028
Intelligent monitoring	0.955	0.257	0.764	0.022
N (%)	774 (79.88%)	195 (20.12%)	102 (10.53%)	867 (89.47%)
Latent class probabilities	78.93%	21.07%	11.70%	88.30%

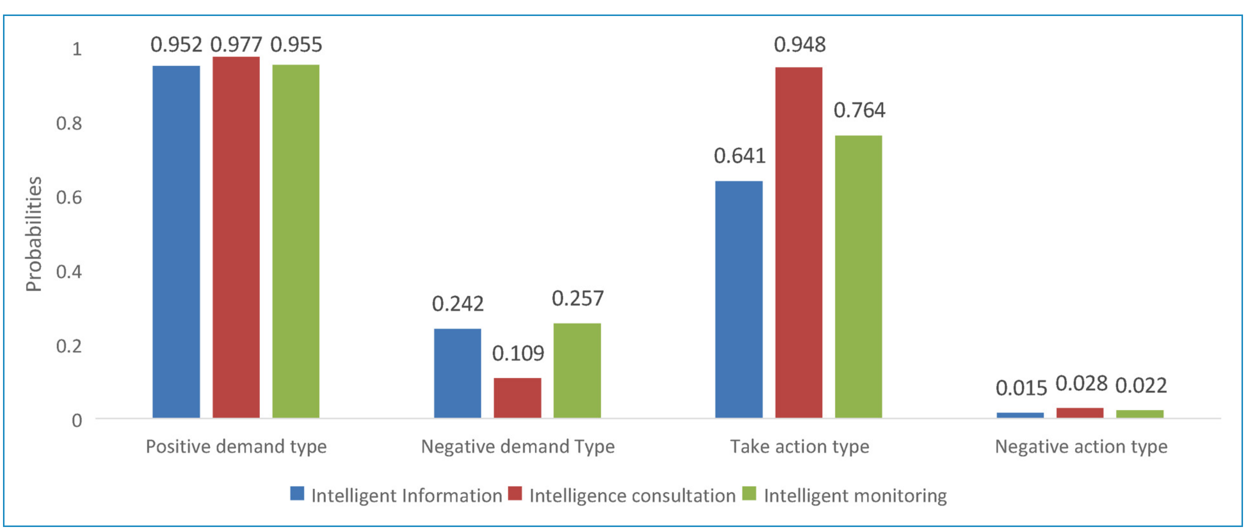

Figure 1. Bar graph of conditional probabilities comparing latent class.

Table 6. Results of binary logistic regression analysis for the "positive demand and taking action" type (OR).

Variables	Positive demand			Take action		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Sex: man (Ref: woman)	1.126 (0.186)	1.103 (0.192)	1.132 (0.206)	0.968 (0.209)	1.047 (0.250)	1.091 (0.272)
Age	1.123 (0.180)	1.095 (0.193)	1.338 (0.245)	1.283 (0.265)	1.134 (0.249)	1.298 (0.297)
Marriage: married (Ref: other)	0.804 (0.251)	0.661 (0.216)	0.722 (0.252)	1.150 (0.464)	0.998 (0.448)	1.257 (0.597)
Child number	1.519*** (0.207)	1.575*** (0.241)	1.491** (0.234)	1.045 (0.112)	0.991 (0.140)	0.961 (0.141)
Education: junior high school (Ref: primary school and below)		1.220 (0.362)	1.299 (0.405)		0.957 (0.375)	0.981 (0.394)
High school/vocational secondary school		0.965 (0.291)	0.971 (0.306)		1.456 (0.615)	1.517 (0.648)
College/junior college and above		2.007 (0.894)	1.873 (0.873)		2.819* (1.552)	2.855* (1.613)
Pre-retirement employment: agriculture related (Ref: no job)		2.053** (0.753)	2.063* (0.776)		4.708*** (2.624)	4.469*** (2.493)
Individually owned business		1.513 (0.541)	1.307 (0.485)		2.839* (1.659)	2.492 (1.441)
Private enterprise		2.138** (0.703)	2.086** (0.708)		0.895 (0.425)	0.798 (0.378)
Public institutions		1.694 (0.769)	1.823 (0.833)		0.538 (0.328)	0.535 (0.329)
Income situation: 3001–5000 (Ref: 3000 and below)		1.580 (0.499)	1.788* (0.616)		2.021 (0.934)	2.425* (1.206)
5001–8000		1.625 (0.565)	1.954* (0.736)		1.030 (0.554)	1.311 (0.745)
8001–12,000		1.364 (0.497)	1.649 (0.656)		1.077 (0.610)	1.424 (0.849)
Over 12,000		1.814 (0.800)	2.007 (0.960)		1.141 (0.717)	1.324 (0.858)
Income sources: child support (Ref: retirement pension)		2.206* (1.060)	2.151 (1.067)		3.879** (2.129)	4.159** (2.487)
Savings, financial investments etc.		2.441* (1.150)	2.210* (1.034)		4.357*** (1.686)	4.354*** (1.764)
Government grants and subsidies		7.083* (8.256)	5.820 (6.880)		1.472 (1.550)	1.397 (1.546)
Labor work		1.635 (0.741)	2.057 (0.969)		3.301** (1.794)	3.932** (2.200)

(continued)

Table 6. Continued.

	Positive demand			Take action		
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Household registration: urban (Ref: rural)		1.349 (0.736)	1.329 (0.841)		0.432 (0.329)	0.408 (0.331)
Housing type: child purchased commercial house (Ref: self-purchased commercial housing)		1.023 (0.297)	0.910 (0.283)		1.022 (0.435)	0.884 (0.400)
Self-built house/rural owned house		0.427** (0.149)	0.431** (0.155)		0.492 (0.234)	0.554 (0.287)
Demolition and resettlement house/unit welfare house		0.968 (0.237)	0.844 (0.214)		1.198 (0.401)	1.053 (0.356)
Rental housing/senior apartment/other		0.824 (0.406)	0.908 (0.450)		1.040 (0.677)	1.006 (0.693)
Medical insurance: NACMI (Ref: self-funded)		4.174 (5.448)	3.898 (6.132)		0.126 (0.261)	0.0909 (0.226)
URRBMI		2.345 (2.732)	2.570 (3.656)		0.257 (0.488)	0.235 (0.544)
UEBMI		1.589 (1.921)	1.727 (2.517)		0.762 (1.462)	0.705 (1.631)
Free medical care		1.091 (1.348)	1.257 (1.857)		0.458 (0.908)	0.452 (1.074)
Community device: yes (Ref: no)		1.774*** (0.376)	1.700** (0.379)		3.500*** (1.624)	3.307** (1.578)
Community promotion: yes (Ref: no)		1.370 (0.333)	1.142 (0.283)		3.544** (2.108)	3.108* (1.841)
Region: central region (Ref: Western region)		1.210 (0.460)	1.316 (0.514)		2.254 (1.330)	2.661* (1.572)
Eastern region		1.046 (0.282)	1.145 (0.318)		2.683** (1.271)	3.002** (1.416)
Chronic diseases number			1.218** (0.103)			1.018 (0.0944)
Self-care ability			0.214*** (0.0710)			0.438*** (0.0866)
Constant	1.921 (0.903)	0.147 (0.215)	5.939 (11.95)	0.0649*** (0.0336)	0.00662** (0.0154)	0.0388 (0.106)
R^2	0.0184	0.0763	0.1373	0.0029	0.1382	0.1700

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Odds ratio, robust standard errors in parentheses.
NACMI: New Agricultural Cooperative Medical Insurance; UEBMI: Urban Employees Basic Medical Insurance; URRBMI: Urban and Rural Residents Basic Medical Insurance.

Table 7. Results of binary logistic regression analysis for service demand and community supply.

Variables	Services demand			Community supply		
	Intelligent information	Intelligence consultation	Intelligent monitoring	Intelligent information	Intelligence consultation	Intelligent monitoring
Sex: man (Ref: woman)	1.193 (0.221)	1.164 (0.226)	0.972 (0.195)	1.081 (0.155)	1.006 (0.149)	1.150 (0.171)
Age	1.226 (0.234)	1.316 (0.265)	1.022 (0.216)	0.867 (0.117)	0.934 (0.134)	0.926 (0.131)
Marriage: married (Ref: other)	0.756 (0.270)	1.096 (0.395)	1.150 (0.422)	0.985 (0.248)	0.905 (0.233)	1.184 (0.300)
Child number	1.311* (0.205)	1.798*** (0.316)	1.489** (0.256)	1.084 (0.0959)	0.966 (0.0889)	1.135 (0.104)
Education: junior high school (Ref: primary school and below)	1.107 (0.351)	1.260 (0.433)	1.364 (0.471)	1.487 (0.368)	1.425 (0.354)	1.160 (0.288)
High school/vocational secondary school	0.900 (0.298)	0.870 (0.297)	0.928 (0.324)	1.492 (0.378)	1.396 (0.361)	1.353 (0.350)
College/Junior college and above	1.428 (0.729)	1.771 (0.873)	2.574* (1.282)	1.292 (0.449)	1.690 (0.626)	1.828* (0.661)
Pre-retirement employment: agriculture related (Ref: no job)	1.657 (0.669)	1.726 (0.719)	2.226* (0.936)	0.725 (0.222)	0.770 (0.243)	1.158 (0.355)
Individually owned business	1.176 (0.440)	1.268 (0.524)	2.300** (0.933)	0.698 (0.212)	0.637 (0.197)	1.035 (0.322)
Private enterprise	1.596 (0.576)	2.436** (0.883)	1.793 (0.652)	0.991 (0.293)	0.836 (0.251)	0.762 (0.229)
Public institutions	1.768 (0.895)	2.580* (1.258)	0.997 (0.476)	0.861 (0.326)	0.453** (0.177)	0.631 (0.244)
Income situation: 3001–5000 (Ref: 3000 and below)	2.073** (0.716)	1.833 (0.679)	1.340 (0.510)	1.275 (0.332)	1.307 (0.346)	1.155 (0.310)
5001–8000	2.267** (0.872)	1.890 (0.740)	1.318 (0.543)	2.088*** (0.590)	1.346 (0.390)	1.128 (0.327)
8001–12,000	2.421** (0.999)	1.664 (0.683)	1.050 (0.455)	1.958** (0.599)	1.164 (0.362)	0.973 (0.304)
Over 12,000	3.638** (1.859)	1.338 (0.637)	1.276 (0.641)	2.061** (0.725)	0.972 (0.356)	0.888 (0.324)
Income sources: child support (Ref: retirement pension)	2.284 (1.202)	1.651 (0.954)	2.127 (1.163)	1.065 (0.386)	1.259 (0.469)	1.261 (0.447)

(continued)

Table 7. Continued.

Variables	Services demand			Community supply		
	Intelligent information	Intelligence consultation	Intelligent monitoring	Intelligent information	Intelligence consultation	Intelligent monitoring
Savings, financial investments, etc.	3.851** (2.485)	2.253 (1.131)	1.900 (1.071)	1.394 (0.419)	1.776* (0.533)	0.857 (0.268)
Government grants and subsidies	5.346 (6.299)	4.163 (5.383)	3.152 (3.642)	0.987 (0.592)	1.126 (0.683)	0.200** (0.152)
Labor work	2.002 (0.954)	3.006** (1.569)	1.884 (0.996)	2.055** (0.727)	1.656 (0.575)	1.328 (0.477)
Household registration: urban (Ref: rural)	0.501 (0.422)	1.314 (0.960)	0.747 (0.581)	1.184 (0.668)	0.549 (0.338)	0.947 (0.579)
Housing type: child purchased commercial house (Ref: self-purchased commercial housing)	1.232 (0.422)	1.110 (0.394)	1.162 (0.436)	1.306 (0.338)	0.820 (0.221)	0.740 (0.203)
Self-built house/rural owned house	0.840 (0.324)	0.415** (0.160)	0.701 (0.285)	1.123 (0.337)	0.652 (0.194)	0.835 (0.252)
Demolition and resettlement house/unit welfare house	0.935 (0.243)	0.802 (0.209)	1.042 (0.291)	0.853 (0.170)	0.862 (0.178)	1.095 (0.228)
Rental housing/senior apartment/other	1.008 (0.510)	0.677 (0.363)	1.227 (0.688)	0.800 (0.355)	0.293** (0.143)	0.708 (0.315)
Medical insurance: NACMI (Ref: self-funded)	1.964 (3.070)	4.065 (3.681)	1.392 (2.002)	0.410 (0.593)	0.157 (0.293)	0.220 (0.335)
URRBMI	2.867 (3.712)	2.561** (1.176)	2.346 (2.725)	0.332 (0.436)	0.282 (0.490)	0.230 (0.316)
UEBMI	2.403 (3.197)	1.518 (0.531)	2.141 (2.556)	0.229 (0.301)	0.165 (0.286)	0.205 (0.281)
Free medical care	1.228 (1.653)	–	1.603 (1.948)	0.186 (0.246)	0.186 (0.323)	0.269 (0.370)
Community device: yes (Ref: no)	1.509* (0.349)	1.579* (0.384)	1.790** (0.428)	1.395* (0.252)	1.183 (0.228)	1.345 (0.265)
Community promotion: yes (Ref: no)	1.122 (0.292)	1.036 (0.282)	1.023 (0.286)	1.848*** (0.403)	2.628*** (0.646)	1.833** (0.437)
Region: central region (Ref: western region)	1.203 (0.489)	2.640** (1.136)	0.861 (0.361)	1.135 (0.365)	0.710 (0.235)	1.135 (0.363)
Eastern region	0.995 (0.294)	1.892** (0.553)	1.124 (0.340)	1.160 (0.277)	0.968 (0.232)	1.273 (0.301)
Chronic diseases number	1.152* (0.0961)	1.180* (0.106)	1.141 (0.102)	1.034 (0.0617)	1.015 (0.0636)	0.993 (0.0614)

(continued)

Table 7. Continued.

Variables	Services demand			Community supply		
	Intelligent information	Intelligence consultation	Intelligent monitoring	Intelligent information	Intelligence consultation	Intelligent monitoring
Self-care ability	0.281*** (0.0795)	0.175*** (0.0682)	0.309*** (0.0976)	0.717** (0.0938)	0.715** (0.0969)	0.724** (0.0958)
Constant	9.424 (18.56)	4.694 (7.941)	7.070 (13.50)	1.330 (2.115)	6.818 (13.57)	1.841 (3.066)
R^2	0.1107	0.1607	0.1192	0.0506	0.0655	0.0424

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Odds ratio, robust standard errors in parentheses.
NACMI: New Agricultural Cooperative Medical Insurance; UEBMI: Urban Employees Basic Medical Insurance; URRBMI: Urban and Rural Residents Basic Medical Insurance.

care ability emerged as significant variable for all three services.

Regarding community supply outcomes, the analysis indicated that income situation significantly positive effects the supply of II services. Furthermore, income sources variable showed significantly association with the supply of II and IM services. Pre-retirement employment of public institutions showed negative effect on IC services compared to no job person (OR = 0.453, $p < 0.05$). Rental housing, elder housing, and other housing types were associated with a reduced supply response for IC services (OR = 0.306, $p < 0.05$). Notably, both community promotion and self-care ability variables exhibited significant effects on all three types of services.

Discussion

The present study offers a comprehensive examination of the demand, utilization, and supply of smart senior services among older adults, building on the understanding that integrating smart medical care into home-based systems represents an effective approach to addressing home healthcare issues.[9] On the demand side, the types of potential demand and actual utilization were delineated, and the facilitators of positive subgroups were explored using the Andersen's behavioral model. Simultaneously, we analyzed the imbalance between supply and demand for smart senior care services and identified factors influencing both demand and supply. This study provides a depth analysis of the three existing service types of smart senior care through a systematic investigation of supply, demand and utilization. It depicts the current status of diverse elderly population regarding smart senior services, thereby contributing to the optimization of smart senior care services.

According to the LCA, 79.88% of the respondents belonged to the "positive demand" type, exhibiting a robust need for all three smart ageing services in their daily lives. This trend may be attributed to the increased publicity and promotion of smart ageing in recent years, coupled with the growing interest and acceptance of smart technology among older adults as the Internet access becomes more widespread. However, in terms of actual utilization, 89.47% of participants fell into the "negative action" type, suggesting that most older adults underutilize these services. As a technologically marginalized group, older adults often struggle with using smart products.[38,39] This underutilization could be due to various barriers, including the high cost and difficulty accessing community smart senior care services, unfamiliarity with new technologies, lack of awareness about available services, or other personal reasons that hinder practical adoption.[40] Notably, IC services exhibited the highest probability of utilization among older adults, aligning with their preference for smart senior care in healthcare settings.[5] Our results revealed that the "positive need–negative action" type accounted for 69.35% of the participants, indicating a need for increased efforts to popularize and educate this group. Therefore, opportunities for community sharing of information about smart home technology can be used to improve awareness and discussion among older adults.[41] This would enhance their understanding of smart ageing services and lower the threshold for utilizing community-based smart ageing services.

We examined the factors influencing positive demand, action, and supply of smart ageing services among older adults using the Andersen's behavioral model. First, among predisposing factors, only the number of children positively impacted demand, encompassing both positive demand type and actual utilization. This aligns with previous studies that suggest the use of senior products by older adult is an intergenerational interactive process.[42] Children's use of internet technology may stimulate older adults' demand for such services. However, our findings also reveal that the effect of children on actual utilization was negative but nonsignificant. This concurs with Dermody et al.,[41] who concluded that older adults with less family support were more likely to receive advanced smart care. Simultaneously, our results imply that children may not provide sufficient guidance to promote utilization behavior among older adults.[43] Therefore, policies promoting smart ageing should prioritize the role of family support and encourage family members to educate older adults on understanding and using smart technology for ageing services. Furthermore, special attention should be paid to older individuals living alone.[24]

Second, regarding enabling factors, older adults with higher education levels tend to be more likely to take action and utilize smart ageing services. This is primarily because individuals with more education often have superior access to and comprehension of information, are more acquainted with modern technology and digital tools, and are more likely to grasp the concepts and practices associated with smart ageing services. Consequently, they are more inclined to take action and utilize these services. Simultaneously, older adults with higher education levels are likely to possess better health literacy and be more concerned about their health and quality of life, thereby motivating them to adopt positive measures and to use community-based smart ageing services for health monitoring and improvement. Therefore, augmenting digital literacy and digital health literacy among older adults could lead to increased utilization of smart ageing services.[44] It is thus recommended that communities enhance the digital literacy of the elderly by organizing volunteers or professionals to provide them with training on the fundamental operation of digital devices, including smartphones and health monitoring devices at community activity center. Combining both income level and sources of income revealed that higher affordability positively influences the demand, utilization, and supply of smart senior services. The findings were consistent with research pointing to affordability as a key factor influencing older people's intention to use digital technology.[14] This is likely due to a financial capacity that facilitates easier access to and willingness to pay for these services, thereby enhancing quality of life. Among insurance factors, only URRBMI facilitated IC demand, presumably because employee health insurance provides better coverage for medical expenses. This finding aligns with that of Du et al. and Yunhua Wang et al.[21,45] who underscore pension security as a crucial factor shaping older adults' preferences for senior care. When financial expenditures are affordable, older adults prefer integrated medical–nursing care. Moreover, as some internet-based medical care is gradually incorporated into medical insurance in China, its economic accessibility has improved, potentially enhancing demand and willingness. Previous research has highlighted cost as the primary determinant of older adults' service utilization decisions.[5,16] Hence, for older adults utilizing smart senior care services, financial subsidies tailored to their financial situation could enhance financial security, and preferential policies for smart senior care services, such as free trials and discounted purchases, could stimulate utilization willingness. With regard to housing type, the findings revealed that self-built houses and rural-owned houses exhibited lower positive demand and lower demand for IC compared to self-purchased commercial housing. In China, this type of housing is mainly located in rural areas, while commercial housing is located in urban areas. This finding may be indicative of the attitudes of the rural population toward smart ageing in the community. Subsequent research could further target smart ageing in rural communities.

From a community perspective, older adults residing in areas with community-provided smart devices are more likely to belong to the "positive demand" and "taking action" types. The availability of smart devices in the community may enhance older adults' life quality, making it easier for them to acquire information related to smart senior care services and augmenting their demand. Community promotional activities encouraged older adults to adopt action-oriented behaviors and are also associated with service supply. Inadequate publicity has been linked to participants' lack of utilization or awareness of these services.[16] Therefore, community- and environmentally oriented supportive information can be used to expand and disseminate health knowledge, promoting older adults to utilize relevant services. In region factor, the eastern region have more mature smart elderly care models, and the results have shown more positive utilization behaviors among the elderly than in the western region. This is consistent with the results of a study in Lanzhou, a region in western China, which found that Lanzhou seniors had very low awareness of smart senior services.[21]

Third, regarding enabling factors, the results indicated that chronic disease status tends to propel older adults toward the positive demand type. This can be attributed to the fact that individuals with multiple chronic diseases often face more intricate health challenges, necessitating comprehensive and personalized health care management services. Consequently, they may have a greater need for community-based smart ageing services that offer support, such as medical monitoring and emergency assistance to cope with complex health conditions.[46] However, despite this demand, utilization may be hampered by the complexity of the disease, difficulties in using the technology for older adults, or fears of incorrect usage. The findings pertaining to self-care ability revealed that it had a negative effect on demand, behavior, and supply, which aligns with the observations made by Huang Q.[24] This may stem from the fact that older individuals with limited functional capacity are more reliant on external assistance and encounter difficulties in independent living, thereby driving a higher demand for senior care services. Moreover, older adults with diverse physical conditions require tailored smart technologies.[47] Research pointed out that information technology can only be successfully introduced into the lives of community-dwelling older people if their needs are truly understood.[48] Therefore, it is suggested that the supply of smart senior care services considers the physical condition of older adults and tailors the services accordingly.

Limitation of the study

There are several limitations in our study. The first limitation of this study is that the use of a convenience sample introduces potential selection bias, limiting the generalizability of findings to broader elderly population or diverse cultural contexts. This may hinder the applicability of results in policy formulation, market strategies, and service design. Secondly, although the selection of variables was grounded in Andersen's behavioral model, other factors pertaining to older adults' characteristics and technological risks (e.g. security concerns, privacy risks) may influence the utilization of smart senior care services. Additionally, there may be variables specifically associated with differences in demand, utilization, and supply. This limitation may compromise the model's explanatory power and restrict a comprehensive understanding of smart senior care service utilization. Third, the reliance on self-reported data in this study poses risks of recall bias, social desirability bias, and personal prejudices, potentially obscuring objective realities and impacting the validity of conclusions. Finally, although cross-sectional studies can suggest causal associations, they cannot establish definitive causal relationships. This constraint necessitates caution in interpreting causal inferences and highlights the need for longitudinal or experimental studies to strengthen causal claims. Future research could track older adults' utilization of smart ageing services following the implementation of policies and community advocacy to further investigate the effects of such interventions. It is also imperative to understand the current situation and challenges in the supply of smart ageing services from the perspective of service providers for a more comprehensive analysis of supply and demand.

Future implications of the study

The present study has significant implications for practical applications in the field of smart senior care services. Based on our findings, several future directions for research and policy interventions can be outlined to further advance the smart senior care model in China.

Enhanced family engagement and support systems: Given the pivotal role of family support in encouraging smart senior care service adoption, the interventions to strengthen family involvement should be developed in depth. This could involve designing family-centered educational programs to raise awareness about the benefits of smart ageing technologies and how to effectively integrate them into daily care routines.

Community-led support and promotion initiatives: Community support and promotion efforts should be focused on creating age-friendly environments that prioritize digital inclusion and enhancing digital health literacy among seniors. This includes training community leaders and volunteers, offering workshops and training sessions tailored to seniors' needs, and leveraging existing community networks to disseminate information about smart ageing services.

Personalization and financial solutions: Emphasis should be placed on the development of personalized smart ageing services and applications. This includes leveraging data analytics and artificial intelligence to create customized recommendations based on individual health conditions, preferences, and lifestyles. At the same time, the preferential policies and financial subsidies are recommended to incentivize service use. The collaboration between governments, healthcare providers, and technology companies will be crucial in designing and implementing sustainable funding models that support the widespread adoption of smart ageing technologies.

Conclusion

This study explored the development of smart ageing services from three perspectives including the demand, utilization, and supply of smart senior services among older adults. The persons with high demand but low utilization type comprised the largest proportion of older people, suggesting that older adults have a strong demand for smart ageing services but limited action owing to the challenge of smart senior care services remains a serious problem. In addition, the factors influencing smart senior care services were explored based on Andersen's behavioral model. The results suggested that attention should be paid to the role of family support in encouraging the use of smart senior care services. Preferential policies should be established to provide financial subsidies for service use. Communities need to expand their support and promotion of smart ageing services, focusing on enhancing digital health literacy among seniors to facilitate product utilization. Furthermore, personalized recommendations and applications tailored to the physical conditions of older adults are essential.

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